Electrical Power and Energy Systems 158 (2024) 109973

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Distributed management of energy communities using stochastic profile steering

Juan Camilo López [a,*], Aditya Pappu [a], Gerwin Hoogsteen [a], Johann L. Hurink [a], Marcos J. Rider [b]

[a] EDGE Research Center, Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS), University of Twente, Drienerlolaan 5, Enschede, 7500 AE, The Netherlands

[b] Department of Systems and Energy (DSE), School of Electrical and Computer Engineering (FEEC), University of Campinas (UNICAMP), Av. Albert Einstein Nº400, Campinas, CEP 13083-852, São Paulo, Brazil

ARTICLE INFO

Keywords:
Distributed energy management system
Energy communities
Flexible energy assets
Probabilistic grid limits
Stochastic profile steering

ABSTRACT

This paper presents a novel approach for distributed management of energy communities. The proposed method utilizes a stochastic profile steering algorithm as a greedy heuristic. The optimization process considers random parameters such as local forecasted demand, photovoltaic (PV) production, and the initial energy of electric vehicles (EVs) as embedded scenarios. Profile steering coordinates the flexible electricity assets within an energy community by determining the contribution of each prosumer's profile to the average value of the objective function. It iteratively selects the prosumer that contributes the most until no further improvements can be made. This process scales linearly with the number of controllable prosumers and can achieve various community-level objectives, such as maximizing self-sufficiency or minimizing aggregated cost-of-energy, even when dealing with non-convex optimization problems for modeling each prosumer's local energy management system. The outcome of the proposed method optimizes the average value of the community's objective while ensuring that grid limitations are met within a specified probability. The proposed method is evaluated through simulations involving small-scale communities (5 households) and large-scale communities (100 households). The results demonstrate the efficiency, flexibility, and scalability of the proposed method, as well as its ability to reschedule the aggregated demand to ensure that grid limits are not violated with at least a 95% probability.

1. Introduction

Electric vehicles (EVs), renewable energy sources (RESs), and battery energy storage systems (BESSs) are becoming increasingly accessible for homes and small businesses. The intelligent coordination of multiple prosumers who own such flexible energy assets is a logical next step in integrating renewable energy into smart grids [1]. This coordination is convenient for distribution system operators (DSOs), as it makes it easier to manage the high penetration of distributed generation (DG) and to reduce the needed upgrades to their networks [2]. Prosumers also benefit from it, as it makes it easier to sell excess energy back to the grid and participate in energy markets while meeting their own energy needs [3].

As a result, the concept for energy community emerges, and it stems from the definition given by [4] which describes energy communities as *non-commercial legal entities, based on open and voluntary participation, which are autonomous, and effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity*. This is a broad definition which does not require a local sharing interaction between agents, but it asks for a physical proximity among them and the presence of renewable energy resources. Hence, For the sake of clarity, in our study, we define an energy community as a group of prosumers interconnected within the same electrical network, sharing a common interest in their aggregated energy usage.

In literature, several works propose intelligent management strategies for energy communities using centralized approaches [5–10]. Here, a central controller collects information from prosumers and schedules the operation of flexible electricity assets based on selected objectives and constraints. The controllable devices follow the profile sent by the central agent. This profile can be defined based on price signals, market rules, and short-term load and RES forecasts. Discrepancies between the planned and the realized profile are settled by the main grid. However, such centralized approaches can be inconvenient as they can potentially violate privacy concerns and be a single point of data vulnerability. They may also be less adaptable and scalable than decentralized and distributed methods for large energy communities [11].

* Corresponding author.
E-mail address: j.c.lopezamezquita@utwente.nl (J.C. López).

https://doi.org/10.1016/j.ijepes.2024.109973
Received 29 June 2023; Received in revised form 21 February 2024; Accepted 30 March 2024
Available online 6 April 2024

Distributed intelligent aggregation may be a more suitable approach in this context. Many of these solutions are based on multi-agent systems (MAS) and mathematical decomposition techniques. MAS strategies distribute the process among agents, such as prosumers, aggregators, DSOs, and regulators, allowing them to operate independently under their own rules and constraints. In [12,13], the authors proposed a MAS for energy communities, where prosumers establish their consumption patterns based on individual preferences, and a community manager agent uses these signals to trade with external retailers. However, the method in [12,13] does not consider consensus among the agents, i.e., the internal optimization process made by each residential agent is not influenced by the others'. A similar work that considers the stochastic nature of the problem is proposed in [14], but the consensus among agents is still not considered. In [15], the authors proposed a MAS approach in a multi-layer framework; however, the strategic behavior of prosumers is based on hard-to-obtain parameters that establish the agents' sensitivity to price signals. MAS approaches allow agents to share limited information for mutual benefit, such as price signals from regulators and capacity limits from DSOs. MAS-based approaches are often favored for distributed management of energy communities due to their scalability and flexibility [13]. Security oriented [16,17] and event-based [18] methods have also been proposed in the past. However, the limited interaction among agents in previous works can make it difficult to guarantee community-level optimality and grid-limit feasibility, especially when forecast inaccuracies are not taken into account.

On the one hand, mathematical decomposition techniques, such as Benders' decomposition [19,20] and the alternating direction method of multipliers (ADMM) [21–24], have also been employed for aggregating energy communities. These iterative methods break down the centralized optimization model into smaller subproblems that are solved by individual agents. Bi-level [25] and tri-level [26] optimization models can also be decomposed to integrate multiple objectives. For instance, prosumers within the energy community can minimize their local emissions while the aggregator aims to maximize its profit in energy trading. However, the convergence of mathematical decomposition techniques to an optimal solution depends on the convexity of the centralized version of the problem. Therefore, if non-linear (and even non-analytical) constraints are necessary to model the optimization problem solved by each prosumer, these techniques cannot be applied unless a convex version of the problem can be formulated.

On the other hand, previous works on distributed management of energy communities have overlooked the crucial aspect of uncertainty. Solely relying on average values of random variables, such as EV state-of-charge (SoC), short-term demand, and PV generation forecast, using deterministic approaches can lead to grid limit violations if the actual outcomes differ from the expected ones, as demonstrated in [27]. Mathematical programming enables the incorporation of uncertainty through stochastic and robust approaches. However, as shown in [28], existing distributed optimization methods fail to combine the advantages of both approaches to effectively address uncertainties.

In this context, the current state-of-the-art reveals a research gap in distributed optimization methods for energy communities that encompasses: (a) stochasticity, (b) community-level optimization while meeting energy requirements of prosumers, and that is (c) independent of analytical expressions within the energy management system (EMS) of prosumers.

Thus, this paper proposes a novel approach for aggregating distributed energy communities using stochastic profile steering, which is a greedy heuristic algorithm. Profile steering coordinates flexible electricity assets within an energy system by considering the contribution of prosumers to the community's objective function [29]. The proposed stochastic version treats local demand, PV production, and the initial SoC of EVs as random variables with known scenarios and probabilities. The distributed management optimizes the community's objective average value while ensuring grid limitations are met with a given probability. Unlike previous MAS approaches, the proposed decentralized method requires consensus among prosumers' decisions. This enables achieving community-level objectives, such as maximum self-sufficiency or minimum aggregated cost-of-energy, while maintaining feasible operation within grid limits. Additionally, the profile steering algorithm's greedy nature allows the method to converge into a feasible optimized solution without requiring convexity in the prosumers' optimization problem. Although profile steering has been previously applied to solve distributed energy management problems [30,31], this is the first adaptation that considers the stochastic nature of the problem and probabilistic grid limits. Simulations illustrate the characteristics of the proposed method using a small community of 5 households and demonstrate scalability with a large community of 100 households. To emphasize the contribution, details regarding the physical implementation of the proposed method are omitted. However, authors in [32] present an implementation framework, defined as "community flexibility aggregation", which aligns with the proposed method.

The contribution of the paper is: a novel version of the profile steering algorithm as the main strategy for the distributed management of energy communities, considering stochastic optimization and probabilistic grid limits. This novel version of the profile steering algorithm does not require each prosumer's EMS to be represented using convex (or even analytical) expressions. Instead, the algorithm grows linearly with the number of prosumers and achieves community-level objectives, such as maximum self-sufficiency or minimum aggregated cost-of-energy.

2. Methodology

2.1. Notation

All variables and parameters employed in the mathematical programming model are subscripted symbols, where subscript indices represent the dependency on designated sets and superscripts establish the device type. For instance, $e_{n,t}^{\mathrm{BESS}}$ is a BESS-related variable defined for each element $n \in N$ and $t \in T$. Parameters and sets are denoted in uppercase, while variables and indices are presented in lowercase. Vectors (or profiles) are displayed in bold typeface, and subscript * indicates the "optimized value of…".

2.2. Stochastic management of energy communities

In this work, an energy community consisting of $n \in N$ prosumers that own various flexible electricity assets (e.g. EVs, rooftop PV panels with home BESSs, programmable loads, etc.) is considered. Each prosumer owns a local energy controller with its own short-term demand and PV forecasting. Thus, it is assumed that at each time $t \in T$ (where T is a discrete planning horizon), a forecast of the demand ($P_{n,t}^{\mathrm{D}}$) and the PV production ($P_{n,t}^{\mathrm{PV}}$) of each prosumer n is available. In general, forecast models are imperfect and the estimation of random time series is subject to uncertainty. To address this, a set of scenarios $s \in S$ can be used, each containing possible realizations of the random variables with known probabilities, based on which stochastic programming can be applied within the local EMS of the prosumers [33].

As shown in Fig. 1, the profile of prosumer n, for a given scenario s and time period t, is represented by $x_{n,s,t}$, in kW. In this case, the prosumer's total profile is determined by the sum of $P_{n,s,t}^{\mathrm{D}}$, $P_{n,s,t}^{\mathrm{PV}}$, the EV charging schedule, given by $p_{n,s,t}^{\mathrm{EV}}$, and the BESS schedule, given by $p_{n,t}^{\mathrm{BESS}}$. Here, we assume that the BESS profile does not depend on the scenario s because its operation is established once, at the beginning of the planning horizon, and fixed for the rest of the day and for any possible realization of the random variables. As also indicated in Fig. 1, $p_{n,s,t}^{\mathrm{EV}}$ depends on parameters such as the scheduled time-of-arrival (t_n^{arr}), the scheduled time-of-departure (t_n^{dep}), the maximum EV capacity ($\overline{E_n^{\mathrm{EV}}}$), the maximum EV charging power ($\overline{P_n^{\mathrm{EV}}}$), the initial

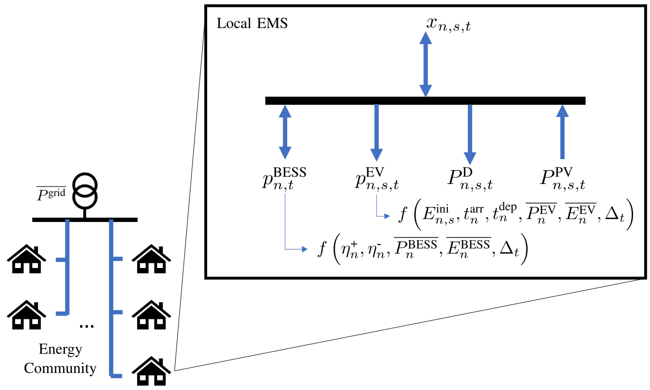


Fig. 1. Illustration of the proposed distributed aggregation of energy communities and the local stochastic EMS approach.

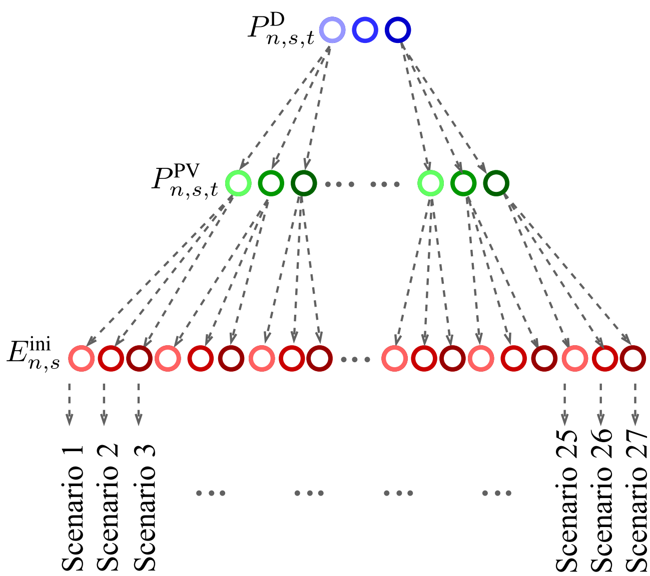


Fig. 2. Scenario generation of the random variables.

energy of the EV at time-of-arrival ($E_{n,s}^{\mathrm{ini}}$), and the duration of the time period (Δ_t) in hours. Note that $E_{n,s}^{\mathrm{EV,ini}}$ is also considered to be a random variable for which scenarios $s \in S$ are given. Likewise, $p_{n,t}^{\mathrm{BESS}}$ depends on the home BESS parameters such as the charging (η_n^+) and discharging (η_n^-) efficiencies, the maximum BESS capacity ($\overline{E_n^{\mathrm{BESS}}}$), the maximum BESS charging power ($\overline{P_n^{\mathrm{BESS}}}$), and the duration of the time period (Δ_t) in hours. Finally, it is assumed that the energy community is connected to the main grid with limited capacity given by $\overline{P^{\mathrm{grid}}}$.

As shown in Fig. 2, each prosumer has a set of stochastic scenarios based on the realizations of the three random parameters: $P_{n,s,t}^{\mathrm{D}}$, $P_{n,s,t}^{\mathrm{PV}}$, and $E_{n,s}^{\mathrm{ini}}$. Assuming independence, the stochastic local EMS uses 27 scenarios with given probabilities represented by $\Pi_{n,s}$. Note that $P_{n,s,t}^{\mathrm{D}}$ and $P_{n,s,t}^{\mathrm{PV}}$ are random time-series defined for the whole planning horizon $t \in T$, whereas $E_{n,s}^{\mathrm{ini}}$ is only defined for the time of arrival (t_n^{arr}). Specifying these scenarios and probabilities is not covered in this paper. They can be obtained from historical data, forecast error analysis, clustering, or expert systems [34].

The mathematical model for the stochastic EMS of energy communities is given below by (1)–(15). Here, $\mu_{x_{n,t}}$ is the average profile of prosumer n calculated by (2). The objective function is defined by the community's (or aggregator's) objective, given by function $F(\cdot)$ in (1). In this case, $F(\cdot)$ depends on the average aggregated consumption (i.e., $\sum_{n \in N} \mu_{x_{n,t}}$) over a specified planning horizon. Note that $F(\cdot)$ does not require being convex, or even analytical. For instance, the objective could be to maximize the use of local RESs, minimize emissions, or maximize profits from participating in electricity markets.

$$\min_{\forall t \in T} \left\{ F\left(\sum_{n \in N} \mu_{x_{n,t}} \right) \right\} \tag{1}$$

Subject to:

$$\mu_{x_{n,t}} = \sum_{s \in S} \Pi_{n,s} x_{n,t,s}; \qquad \forall t \in T, n \in N \tag{2}$$

$$x_{n,t,s} = p_{n,t}^{\mathrm{BESS}+} - p_{n,t}^{\mathrm{BESS}-} + p_{n,s,t}^{\mathrm{EV}} + P_{n,t,s}^{\mathrm{D}} - P_{n,t,s}^{\mathrm{PV}}; \qquad \forall s \in S, t \in T, n \in N \tag{3}$$

$$e_{n,t}^{\mathrm{BESS}} = e_{n,t-1}^{\mathrm{BESS}} + \frac{\Delta_t}{\overline{E_n^{\mathrm{BESS}}}} \times \left(\eta^+ p_{n,t-1}^{\mathrm{BESS}+} - \frac{1}{\eta^-} p_{n,t-1}^{\mathrm{BESS}-} \right); \qquad \forall t \in T|_{t > t_{\mathrm{ini}}}, n \in N \tag{4}$$

$$0 \le e_{n,t}^{\mathrm{BESS}} \le 1; \quad 0 \le p_{n,t}^{\mathrm{BESS}+} + p_{n,t}^{\mathrm{BESS}-} \le \overline{P_n^{\mathrm{BESS}}}; \qquad \forall t \in T, n \in N \tag{5}$$

$$p_{n,t}^{\mathrm{BESS}+} \cdot p_{n,t}^{\mathrm{BESS}-} = 0; \qquad \forall t \in T, n \in N \tag{6}$$

$$e_{n,t,s}^{\mathrm{EV}} = e_{n,t-1,s}^{\mathrm{EV}} + \frac{p_{n,t-1,s}^{\mathrm{EV}}}{\overline{E_n^{\mathrm{EV}}}} \eta_n^{\mathrm{EV}} \Delta_t; \qquad \forall s \in S, t \in T|_{t_n^{\mathrm{arr}} \le t \le t_n^{\mathrm{dep}}}, n \in N \tag{7}$$

$$0 \le e_{n,t,s}^{\mathrm{EV}} \le 1; \qquad \forall s \in S, t \in T, n \in N \tag{8}$$

$$0 \le p_{n,s,t}^{\mathrm{EV}} \le \overline{P_n^{\mathrm{EV}}}; \qquad \forall s \in S, t \in T, n \in N \tag{9}$$

$$p_{n,t,s}^{\mathrm{EV}} = 0; \qquad \forall s \in S, t \in T|_{t \le t_n^{\mathrm{arr}} \text{ or } t > t_n^{\mathrm{dep}}}, n \in N \tag{10}$$

$$e_{n,t,s}^{\mathrm{EV}} = \frac{E_{n,s}^{\mathrm{EV,ini}}}{\overline{E_n^{\mathrm{EV}}}}; \qquad \forall s \in S, t \in T|_{t = t_n^{\mathrm{arr}}}, n \in N \tag{11}$$

$$e_{n,t,s}^{\mathrm{EV}} \ge \frac{E_n^{\mathrm{EV,fin}}}{\overline{E_n^{\mathrm{EV}}}}; \qquad \forall s \in S, t \in T|_{t = t_n^{\mathrm{dep}}}, n \in N \tag{12}$$

Eq. (3) represents the power flow balance within household n, for each time period t and stochastic scenario s. Hereby, the BESS charging schedule is separated into non-negative charging ($p_{n,t}^{\mathrm{BESS}+}$) and discharging ($p_{n,t}^{\mathrm{BESS}-}$) flows. Eqs. (4)–(6) determine the operation of the BESS, based on the state-of-charge given by $e_{n,t}^{\mathrm{BESS}}$ [35]. As previously stated, the equations governing the BESS do not depend on the set of scenarios $s \in S$, as its operation is scheduled once at the beginning and fixed for the rest of the planning horizon. Adopting a fixed BESS profile for the upcoming 24 hours, rather than responding to the random realization of local demand and renewable generation, offers the additional advantage of smoother battery cycling. Additional constraints can be incorporated into the model to further enhance this smoothness, e.g., maximum charging/discharging rates. Consequently, unenforceable cycles and micro-cycling are eliminated, which contributes to the extended cycle life expectancy of electrochemical batteries [36].

Eqs. (7)–(12) are related to the EVs, in which whenever the vehicle is available to charge, i.e., at $t_n^{\mathrm{arr}} \le t \le t_n^{\mathrm{dep}}$, (7) and (8) determine the operation of the EV charger. Naturally, if the EV is not available, zero charging is imposed by (10). (11) defines the initial state-of-charge for each scenario $s \in S$, based on the realization of $E_{n,s}^{\mathrm{EV,ini}}$, and (12) defines the final state-of-charge that must be guaranteed at t_n^{dep}. Parameter $E_n^{\mathrm{EV,fin}}$ is a charging requirement that can be adjusted by each prosumer based on their own preferences.

The standard deviation of each prosumer profile ($\sigma_{x_{n,t}}^2$) is calculated by (13). Therefore, (14) and (15) are the robust constraints for the aggregated demand of the energy community. These constraints can be considered probabilistic constraints because, if a normal distribution of the aggregated demand is assumed, the average value and two standard deviations are guaranteed to stay within grid limits (i.e., within $\pm\overline{P^{\mathrm{grid}}}$) 95% of the time, according to [37].

$$\sigma_{x_{n,t}}^2 = \sum_{s \in S} \Pi_{n,s} \left(x_{n,t,s} - \mu_{x_{n,t}} \right)^2; \qquad \forall t \in T, n \in N \tag{13}$$

$$\sum_{n \in N} \mu_{x_{n,t}} + 2\sqrt{\sum_{n \in N} \sigma^2_{x_{n,t}}} \le \overline{P^{\text{grid}}}; \qquad \forall t \in T \quad (14)$$

$$-\overline{P^{\text{grid}}} \le \sum_{n \in N} \mu_{x_{n,t}} - 2\sqrt{\sum_{n \in N} \sigma^2_{x_{n,t}}}; \qquad \forall t \in T \quad (15)$$

As demonstrated in (1)–(15), the overall energy management of the community is formulated as a two-stage stochastic optimization problem, where certain decisions and state variables depend on the realization of each scenario [38]. These decisions and variables are called "wait-and-see", exemplified by the charging profile of each EV. Others are deployed independently of each realization, categorized as "here-and-now" decisions, such as the operation of the BESSs. Both "here-and-now" and "wait-and-see" decisions and variables are simultaneously optimized through the two-stage stochastic optimization problem to achieve average community-level objectives.

The non-linear non-convex programming model in (1)–(15) represents a centralized stochastic EMS for energy communities. The objective function (1) and the constraints (14) and (15) couple the operation of all the prosumers within the community. Thus, in order to maintain each prosumer's local information private and to make it computationally scalable, a distributed version of the EMS is necessary. Furthermore, since the local stochastic EMS used by each prosumer is non-convex, mathematical decomposition techniques cannot be used without altering the nature of the models.

2.3. Stochastic profile steering

In this subsection, we present a stochastic version of the profile steering algorithm from [29] to distribute the optimization process among prosumers within the energy community. Firstly, we introduce an algorithm for stochastic management of energy communities that ignores grid limits. Next, we introduce a second algorithm that considers grid limits but overlooks community objectives, focusing instead on minimizing the probability of grid violations by the aggregated demand. Finally, we present the stochastic steering algorithm, which integrates the previous two algorithms into a single framework to balance the optimization of community objectives and probabilistic grid limits. It is worth noting that profile steering can also be developed in a hierarchical structure in which multiple energy communities can be distributionally optimized, or even the devices within each household can be considered as independent agents [30]. This extensions will be developed in future research works.

2.3.1. Stochastic EMS disregarding probabilistic grid limits

Let $\boldsymbol{\mu}_{x_n}$ be the average power profile of prosumer $n \in N$, where $\boldsymbol{\mu}_{x_n} = \left\{\mu_{x_{n,1}}, \dots, \mu_{x_{n,|T|}}\right\}$. Assume that $\boldsymbol{\mu}_{\boldsymbol{x}}$ represents the average aggregated profile of the energy community, where $\boldsymbol{\mu}_{\boldsymbol{x}} = \sum_{n \in N} \boldsymbol{\mu}_{x_n}$. Thus, the optimization problem around this profile $\boldsymbol{\mu}_{\boldsymbol{x}}$ is given by the mathematical programming model in (16), in which the grid limits in (14) and (15) are being neglected, and the objective function in (1) is rewritten as $F\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right)$.

$$f\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \begin{cases} \min \left\{F\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right)\right\} \\ \text{s.t.:} \\ \quad (2)\text{–}(12) \end{cases} \qquad (16)$$

An algorithm for distributing (16) among prosumers is shown in Algorithm 1. The initial average profile requested in line 1 can be obtained by solving (16) with an individual objective function for each prosumer, i.e., a fully decentralized approach. Line 2 calculates the aggregated average profile $\boldsymbol{\mu}_{\boldsymbol{x}}$. Parameter $\bar{\delta}$ in line 3 represents the maximum improvement and it is used as the stopping criterion of the iterative process in lines 4 to 11. Lines 6 and 7 determine the candidate average profile $\boldsymbol{\mu}^*_{x_n}$ and its improvement δ^*_n by solving (16) for each agent $n \in N$. Note that in the expression $\boldsymbol{\mu}_{\boldsymbol{x}} - \boldsymbol{\mu}_{x_n} + \bar{\boldsymbol{\mu}}_{x_n}$, both $\boldsymbol{\mu}_{\boldsymbol{x}}$ and $\boldsymbol{\mu}_{x_n}$ are parameters, whereas $\bar{\boldsymbol{\mu}}_{x_n}$ is the decision variable. Hence, the calculations within lines 5 to 7 can be performed independently by each prosumer in a distributed fashion, and hence executed in parallel. In lines 9 and 10, the candidate average profile with the best improvement (i.e., n^*) is determined and the average profile with the best improvement (i.e., $\boldsymbol{\mu}^*_{x_{n^*}}$) is updated. These calculations can be done by an independent aggregator or by a separate agent that acts as the community manager. Finally, the iterative process is repeated until the best improvement $\bar{\delta}$ is lower than a given small threshold ϵ. Algorithm 1 is a generalized stochastic adaptation of the profile steering approach, in which scenarios and probabilities are necessary to calculate the average profiles. Note that the nature of the problem in Line 6 does not need to be convex or even analytical. As long as the optimization process is able to provide feasible solutions for $\boldsymbol{\mu}^*_{x_n}$, Algorithm 1 will return a better solution that the initial average profile [29].

Algorithm 1 Stochastic profile steering for energy communities, disregarding grid limits

```
1: Request an initial average profile μ_{x_n} of each prosumer
2: μ_x = Σ_{n∈N} μ_{x_n}
3: δ̄ ← ∞                                    ▷ Initialize improvement
4: while δ̄ < ϵ do
5:     for n ∈ N do
6:         μ*_{x_n} ← argmin_{μ̄_{x_n}} f(μ_x − μ_{x_n} + μ̄_{x_n})
7:         δ*_n ← f(μ_x) − f(μ_x − μ_{x_n} + μ*_{x_n})
8:     end for
9:     n* ← arg max_n δ*_n
10:    μ_{x_n} ← μ*_{x_{n*}}, δ̄ ← δ*_{n*}
11: end while
12: Return μ_x
```

2.3.2. Stochastic EMS considering probabilistic grid limits, disregarding the community objective

Let $\boldsymbol{\sigma}_{x_n}$ be the standard deviation of the power profile of prosumer $n \in N$, where $\boldsymbol{\sigma}_{x_n} = \left\{\sigma_{x_{n,1}}, \dots, \sigma_{x_{n,|T|}}\right\}$. Assume that $\boldsymbol{\sigma}_{\boldsymbol{x}}$ represents the standard deviation of the aggregated profile of the energy community, where $\boldsymbol{\sigma}_{\boldsymbol{x}} = \sqrt{\sum_{n \in N} \boldsymbol{\sigma}^2_{x_n}}$, assuming i.i.d. In this case, it is possible to use a different optimization function $g\left(\boldsymbol{\mu}_{\boldsymbol{x}}, \boldsymbol{\sigma}_{\boldsymbol{x}}\right)$, given by (17), which aims at minimizing the violation of probabilistic grid limits. Hence, the original community objective $F(\cdot)$ is disregarded. Algorithm 2 presents the adapted version of the stochastic profile steering used to minimize grid limit violations. Note that Algorithm 2 is similar to Algorithm 1, with the additional updating of the standard deviation for each prosumer's profile $\boldsymbol{\sigma}_{x_n}$, calculated using (13).

$$g\left(\boldsymbol{\mu}_{\boldsymbol{x}}, \boldsymbol{\sigma}_{\boldsymbol{x}}\right) = \begin{cases} \sum_{t \in T} \max \left\{ \sum_{n \in N} \mu_{x_{n,t}} + 2\sqrt{\sum_{n \in N} \sigma^2_{x_{n,t}}} - \overline{P^{\text{grid}}}, \right. \\ \qquad \left. -\overline{P^{\text{grid}}} - \sum_{n \in N} \mu_{x_{n,t}} + 2\sqrt{\sum_{n \in N} \sigma^2_{x_{n,t}}}, 0 \right\} \\ \text{s.t.:} \\ \quad (2)\text{–}(13) \end{cases} \qquad (17)$$

If a feasible solution for problem $g\left(\boldsymbol{\mu}_{\boldsymbol{x}}, \boldsymbol{\sigma}_{\boldsymbol{x}}\right)$ exists, specific limits can be imposed on each prosumer $n \in N$ that contributes to the optimization of (17), via (18) and (19):

$$\overline{P^{\text{grid}}_n} = \overline{P^{\text{grid}}} - \sum_{n' \in N|_{n' \neq n}} \mu_{x_{n',t}} - 2\sqrt{\sum_{n' \in N|_{n' \neq n}} \sigma^2_{x_{n',t}}}; \qquad \forall n \in N \quad (18)$$

$$\underline{P^{\text{grid}}_n} = \overline{P^{\text{grid}}} + \sum_{n' \in N|_{n' \neq n}} \mu_{x_{n',t}} - 2\sqrt{\sum_{n' \in N|_{n' \neq n}} \sigma^2_{x_{n',t}}}; \qquad \forall n \in N \quad (19)$$

Algorithm 2 Stochastic profile steering with probabilistic grid limits, disregarding the community objective

```
Request an initial μ_{x_n} and σ_{x_n} of each prosumer
μ_x = Σ_{n∈N} μ_{x_n}, σ_x = Σ_{n∈N} σ_{x_n}
δ̄ ← ∞                                        ▷ Initialize improvement
while δ̄ < ε do
    for n ∈ N do
        μ*_{x_n}, σ*_{x_n} ← argmin_{μ̄_{x_n}} g(μ_x − μ_{x_n} + μ̄_{x_n}, σ_x − σ_{x_n} + σ̄_{x_n})
        δ*_n ← g(μ_x, σ_x) − g(μ_x − μ_{x_n} + μ*_{x_n}, σ_x − σ_{x_n} + σ*_{x_n})
    end for
    n* ← arg max_n δ*_n
    μ_{x_n} ← μ*_{x_{n*}}, σ_{x_n} ← σ*_{x_{n*}}, δ̄ ← δ*_{n*}
end while
Return μ_x and σ_x
```

Eventually, these values $\overline{P_n^{\mathrm{grid}}}$ and $\underline{P_n^{\mathrm{grid}}}$ can be used to impose local probabilistic limits per prosumer as:

$$\mu_{x_{n,t}} + 2\sigma_{x_{n,t}} \leq \overline{P_n^{\mathrm{grid}}}; \qquad \forall n \in N \tag{20}$$

$$-\underline{P_n^{\mathrm{grid}}} \leq \mu_{x_{n,t}} - 2\sigma_{x_{n,t}}; \qquad \forall n \in N \tag{21}$$

2.3.3. Stochastic EMS considering probabilistic grid limits

Algorithm 3 summarizes the complete deployment of the proposed stochastic profile steering for energy communities, considering both the community objective and probabilistic grid limits. In Line 1, Algorithm 1 is used to optimize the operation of the community disregarding grid limits. Then, the amount of probabilistic grid violations are assessed by g^* in line 2. As indicated in lines 3 to 7, if grid violations exist (i.e., if $g^* > 0$), Algorithm 2 is used for searching for a feasible solution. Otherwise, the updated values of $\boldsymbol{\mu_x}$ and $\boldsymbol{\sigma_x}$ are returned and the algorithm ends. Then, from line 8 onward the stochastic profile steering algorithm is used to optimize the aggregated profile considering the imposed local probabilistic limits per prosumer given by (20) and (21). Note that in every new iteration, line 11 updates the local limits based on the updated profiles. Since these limits are added to the optimization model as new constraints (see line 12), the average profile plus and minus two standard deviations is bounded by $\overline{P_n^{\mathrm{grid}}}$ and $\underline{P_n^{\mathrm{grid}}}$. The computations in lines 11 to 13 can be deployed in parallel by each prosumer independently.

The relationship between the three algorithms presented in this paper is shown in Fig. 3. All three algorithms have similar computational complexity, as they each require optimizing the local stochastic EMS for each prosumer. This optimization can be achieved using classical non-linear programming methods or modern heuristics. However, the overall computational burden of profile steering grows only linearly with the number of prosumers, making it highly scalable [30]. Finally, since the centralized version of the problem is bounded, convergence is guaranteed because, eventually, the individual improvements will not be able to reduce the incumbent best value of the objective function beyond the threshold. This does not imply that the optimal solution of the centralized version of the model has been found; instead, it indicates that the decentralized optimization process has reached a consensus, where the community-level objective cannot be further improved by any individual contributions. Given that global optimality is not guaranteed, the profile steering algorithm can be considered a greedy heuristic approach. Its advantages include its reliance on deterministic methods (eliminating the need for random exploration) and its structure is suitability for distributed control.

3. Tests and results

In order to show the performance of the proposed method, a small-scale energy community with 5 households is used in this subsection

Algorithm 3 Stochastic profile steering with probabilistic grid limits

```
1: Call Algorithm 1 and calculate σ_{x_n} using (13)
2: g* ← Σ_{t∈T} max{ Σ_{n∈N} μ_{x_{n,t}} + 2 sqrt(Σ_{n∈N} σ²_{x_{n,t}}) − P̄^grid, −P̄^grid − Σ_{n∈N} μ_{x_{n,t}} + 2 sqrt(Σ_{n∈N} σ²_{x_{n,t}}), 0 }
3: if g* > 0 then
4:     Call Algorithm 2
5: else
6:     Return μ_x and σ_x
7: end if
8: δ̄ ← ∞                                        ▷ Initialize improvement
9: while δ̄ < ε do
10:    for n ∈ N do
11:        Calculate P̄_n^grid and P_n^grid (underlined) using (18) and (19)
12:        μ*_{x_n} ← argmin_{μ̄_{x_n}} { f(μ_x − μ_{x_n} + μ̄_{x_n}) | (20) and (21) }
13:        δ*_n ← f(μ_x) − f(μ_x − μ_{x_n} + μ*_{x_n})
14:    end for
15:    n* ← arg max_n δ*_n
16:    μ_{x_n} ← μ*_{x_{n*}}, σ_{x_n} ← σ*_{x_{n*}}, δ̄ ← δ*_{n*}
17: end while
18: Return μ_x and σ_x
```

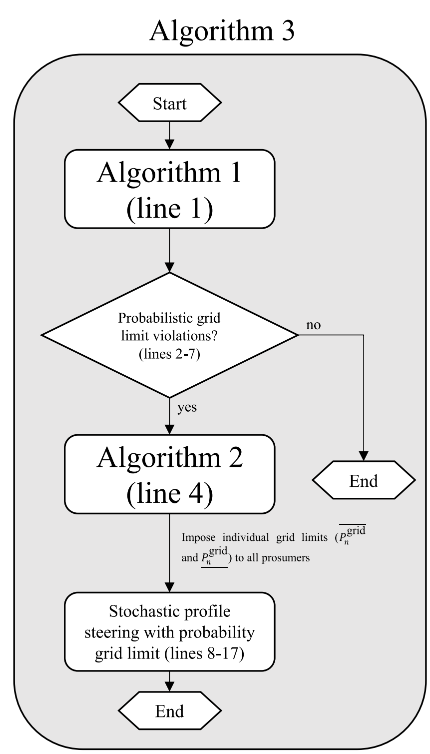


Fig. 3. Relationship between the proposed algorithms.

(see Fig. 4). Hereby, each household contains different configurations of flexible electricity assets (e.g., household A0 owns a rooftop PV, whereas household A3 owns a rooftop PV with BESS and an EV). The used sizes and EV scheduling information are shown in Table 1. Table 1 presents the electricity requirements of the prosumers. Notably, the maximum demand $\overline{P_n^{\mathrm{D}}}$ and PV generation $\overline{P_n^{\mathrm{PV}}}$ represent the highest values from both day-ahead forecasts. However, each prosumer possesses a unique load profile that is only known to its local EMS since these values are not shared in the distributed control process. As illustrated in Fig. 2, each local EMS establishes its own set of stochastic scenarios (and their probabilities) based on the realizations of the three random

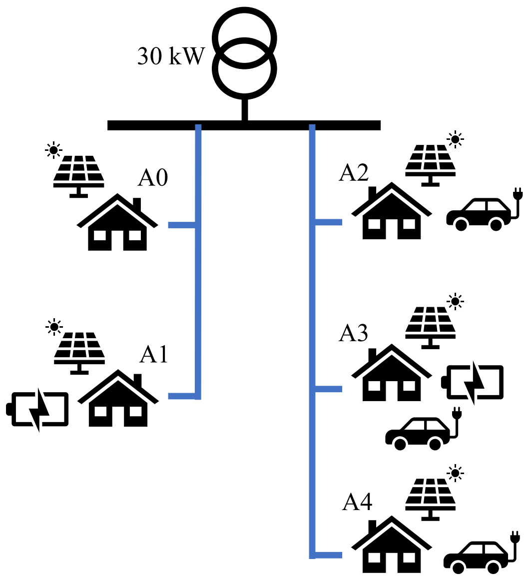


Fig. 4. Small-scale energy community with 5 households, multiple flexible electricity assets, and $\overline{P^{\rm grid}} = 30\,\rm kW$.

Table 1
Parameters of the small-scale energy community in Fig. 4.

Household (n)	A0	A1	A2	A3	A4
$\overline{P_n^{\rm D}}$ [kW]	9.1	9.6	5.5	8.5	8.5
$\overline{P_n^{\rm PV}}$ [kW]	9.2	8.1	7.2	7.7	7.5
$\overline{E_n^{\rm BESS}}$ [kWh]	–	50.0	–	20.0	–
$\overline{P_n^{\rm BESS}}$ [kW]	–	10.0	–	10.0	–
$\overline{E_n^{\rm EV}}$ [kWh]	–	–	50.0	50.0	50.0
$\overline{P_n^{\rm EV}}$ [kW]	–	–	7.7	7.7	5.0
$t_n^{\rm arr}$ [time]	–	–	16:15 h	17:00 h	14:45 h
$t_n^{\rm dep}$ [time]	–	–	06:00 h	08:00 h	09:15 h

variables: $P_{n,s,t}^{\rm D}$, $P_{n,s,t}^{\rm PV}$, and $E_{n,s}^{\rm ini}$, for each $n \in N, s \in S$. Furthermore, a grid limit of $\overline{P^{\rm grid}} = 30\,\rm kW$ has been imposed. The discrete planning horizon T consists of 96 intervals of 15 min for day-ahead planning. Other parameters, not given in Table 1, are $\eta_n^+ = 0.90$, $\eta_n^- = 0.98$, $\eta_n^{\rm EV} = 0.90$, for all $n \in N$ and $\delta_t = 0.25\,\rm h$, for all $t \in T$. The final charging requirement is given by $E_n^{\rm EV,fin} = \overline{E_n^{\rm EV}}$ which guarantees that all EVs must be fully charged at $t_n^{\rm dep}$, for all $n \in N$. Simulations have been run using a 32-core server with Intel(R) Xeon(R) CPU E5-2630 v3 @ 2.40 GHz, with 128 GB of RAM. The non-linear programming solver `ipopt` [39] has been used to solve the optimization models within the algorithms. Note that `ipopt` does not guarantee global optimality. However, as the proposed approach is a greedy algorithm, it will converge to an optimized solution for the problem as long as the local solutions remain feasible.

For this subsection, the objective of the community is to maximize self-sufficiency, which can be attained by setting $F\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \|\boldsymbol{\mu}_{\boldsymbol{x}}\|_2^2$ in (16). An initial schedule for each prosumer is obtained by using an individual objective function, per prosumer, given by $F_n\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \min\left\{\|\boldsymbol{\mu}_{\boldsymbol{x}_n}\|_2^2\right\}, \forall n \in N$. Three different studies have been conducted:

Case 1: optimized distributed energy management neglecting probabilistic grid limits (i.e., Algorithm 1);

Case 2: distributed energy management with probabilistic grid limits but neglecting the objective of the community (i.e., Algorithm 2);

Case 3: optimized distributed energy management with probabilistic grid limits (i.e., Algorithm 3).

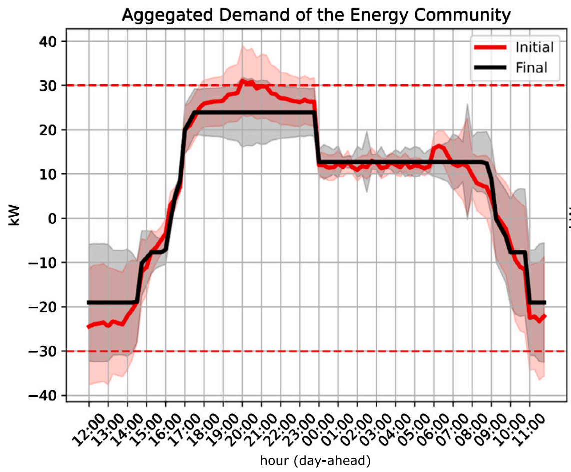
The top graph in Fig. 5(a) compares the initial aggregated demand (in red) with the final optimized demand (in black) of the energy community after solving Case 1. The comparison includes the shadows that depict two times the standard deviation of both time-series, representing 95% of the plausible realizations. The grid limits $\overline{P^{\rm grid}} = \pm 30\,\rm kW$ are depicted by two red dashed lines. The shapes of the initial aggregated profile and the distributed solution are similar, but the final profile has a smoother behavior imposed by the maximization of the community's self-sufficiency. During peak demand times (from 18:00 h to 23:00 h) and peak PV generation times (from 10:00 h to 14:00 h), the initial profile has more pronounced peaks and valleys. This leads to a higher likelihood of the average initial aggregated demand violating grid limits around 20:00 h and a high chance of non-compliance at noon. Despite the solution improving the likelihood of avoiding grid violations in Case 1, there are still chances of non-compliant aggregated profiles since probabilistic grid limits are not imposed by Algorithm 1.

The middle graph in Fig. 5(b) shows the results of Case 2, which minimizes the probability of grid violations by rescheduling consumption from the afternoon and around 20:00 h to late at night. Moreover, grid violations at noon are also minimized by increasing the magnitude of the power used to charge the available BESS at that time. The bottom graph in Fig. 5(c) shows the solution obtained for Case 3, which further optimizes the aggregated profile considering the objective of the community and imposed limits. The final profiles for Cases 2 and 3 are very similar. However, one can notice that variance of the final solution is reduced during the evening and increased in the morning when the probability of grid violations is almost zero, resulting in an aggregated profile that maximizes of self-sufficiency with a 95% probability of avoiding grid violations.

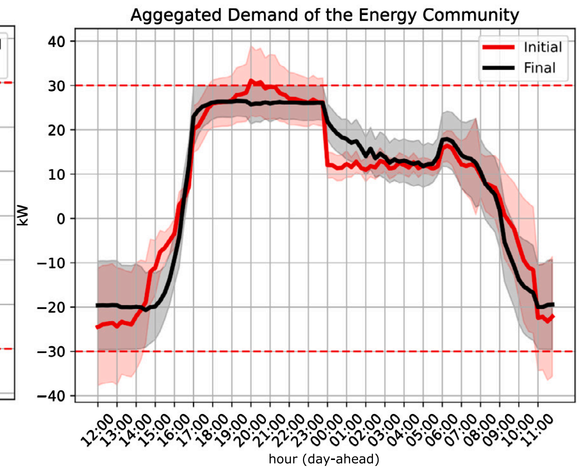
Fig. 6 compares different individual scheduling profiles for household A3, which has a PV panel, a home BESS, and an EV. The initial profile (see Fig. 6(a)) flattens average consumption in the evening and night and distributes variance evenly across scenarios. The BESS profile shows that it charges the most around noon and discharges in the evening to maximize the use of PV generation during peak demand. The EV profiles show that it starts charging at 23:00 h with low intensity, and exponentially increases to be fully charged by 08:00 h. The BESS is also slightly charged during the night such that it is able to prevent increasing the average demand in the morning when non-controllable consumption is high and PV is not yet available.

The results of three distinct cases are also shown in Fig. 6. In Case 1, Fig. 6(b) displays a less flattened consumption pattern, which is attributed to the influence of the other prosumers. This leads to a deeper charging and discharging of the BESS during the course of the day. Furthermore, the charging profiles associated with the EV are mostly dependent on the initial state-of-charge, whereas the influence of the demand and the PV forecast errors is very small. Case 2, depicted in Fig. 6(c), presents a different utilization of the flexible electricity assets. In this scenario, the objective is no longer to maximize self-sufficiency, but rather to stay within the probabilistic grid limits. This results in the operation of both the BESS and the EV during the peak demand period (i.e. between 17:00 h and 22:00 h) in order to minimize the variance around that time and reduce its impact on the aggregated profile. Finally, Case 3, shown in Fig. 6(d), exhibits a similar configuration as in Case 2. However, in this scenario, the EV has more distinguishable profiles. This is because the probability of grid limit violations during nighttime is negligible, and the algorithm focuses on maximizing self-sufficiency instead of adhering to probabilistic grid limits.

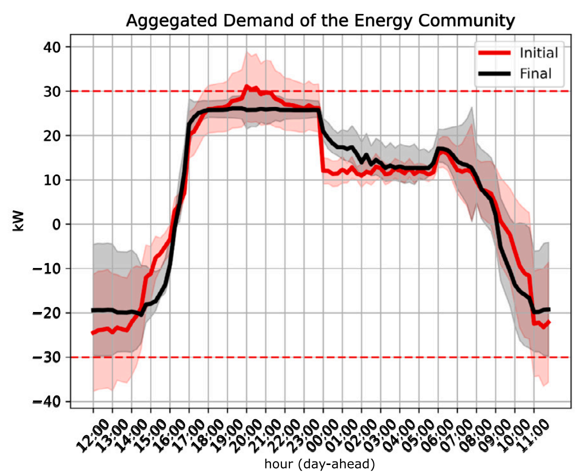
Fig. 7 shows the convergence process for Case 3. Note that three convergence profiles are performed in sequence. Algorithm 1 (blue zone) for initialization, then Algorithm 2 (green zone) for minimizing



(a) **Case 1**: Initial and final profiles.



(b) **Case 2**: Initial and final profiles.



(c) **Case 3**: Initial and final profiles.

Fig. 5. Aggregated demands of the small-scale energy community.

grid violations, and then lines 8–17 (red zone) in Algorithm 3 which performs the profile steering with probabilistic grid limits.

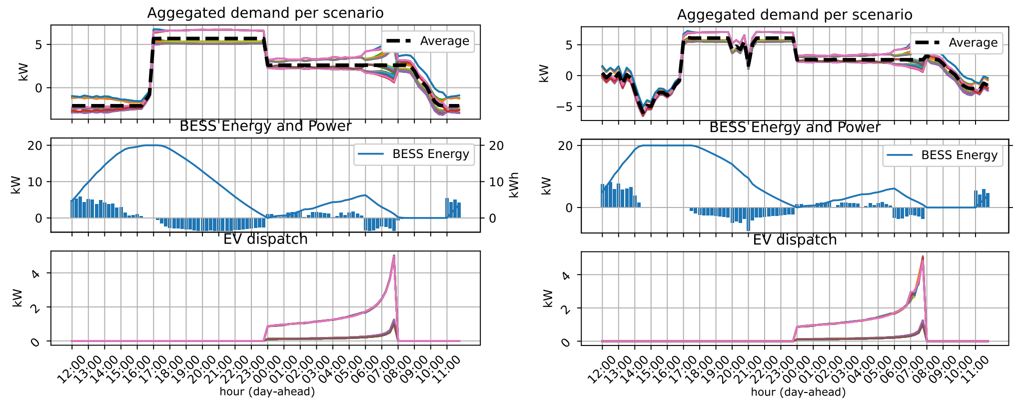
3.1. Minimizing the aggregated cost-of-energy

The objective of stochastic profile steering, as described in Section 2.3, can be adjusted based on community goals. Instead of maximizing self-sufficiency, the aggregator could opt for a minimization of the average aggregated electricity cost while ensuring probabilistic grid limits. Excess energy is sold at the same price of purchase. The cost-of-energy shown in Fig. 8 is used to penalize residential consumption during peak hours, and it is often known as a static time-of-use tariff [40]. Thus, (16) is given by $F\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \boldsymbol{c}^T\boldsymbol{\mu}_{\boldsymbol{x}}$, where $\boldsymbol{c} = \left\{c_1,\ldots,c_{|T|}\right\}$ is the cost-of-energy at each time period, in m.u./kWh. Fig. 9 compares the initial profile with the optimized energy management using Algorithm 3, in which the initial profile is obtained by using an individual objective function, per prosumer, given by $F_n\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \min\left\{\boldsymbol{c}^T\boldsymbol{\mu}_{\boldsymbol{x}_n}\right\}, \forall n \in N$. As expected, consumption during peak demand is heavily minimized due to the time-of-use tariff. However, the initial approach violates grid limits at 17:00 h, at 23:00 h, and even at noon with a probability higher than 60%. The final optimized profile, on the other hand, maintains the aggregated profile within grid limits, while reducing the average consumption as much as possible when the cost-of-energy is at its highest (i.e., between 17:00 h and 21:00 h).

3.2. Large-scale energy community with 100 households

To test the scalability of the developed algorithm, an energy community with 100 households has been considered. The objective of the community is to maximize self-sufficiency, which is represented by the function $F\left(\boldsymbol{\mu}_{\boldsymbol{x}}\right) = \|\boldsymbol{\mu}_{\boldsymbol{x}}\|_2^2$ in (16). All households have a diverse set of flexible electricity assets, demand and PV profiles, and EV requirements. Furthermore, the grid limit is $\overline{P^{\text{grid}}} = 300$ kW. Solving this instance using Algorithm 3 in a sequential manner (i.e., one household per time) took 123.2 h. Thus, dividing this sequential simulation across 100 independent controllers results in a practical time of 73.9 min. Additionally, solving the centralized problem using `ipopt` proved infeasible due to reaching the maximum iteration limit without convergence.

The initial (in red) and the final (in black) aggregated profiles are shown in Fig. 10. As can be seen, in the initial decentralized solution, there is a risk of grid limit violations during peak hours (i.e., between 20:00 h and 21:00 h), and most of the energy locally produced in the energy community is not consumed internally, i.e., poor self-sufficiency. On the other hand, the final solution eliminates this risk of



(a) Initial profile of household A3.
(b) Profile of household A3 for Case 1.
(c) Profile of household A3 for Case 2.
(d) Profile of household A3 for Case 3.

Fig. 6. Individual profiles for household A3, including the aggregated demand per scenario, BESS energy and power, and EV dispatch per scenario.

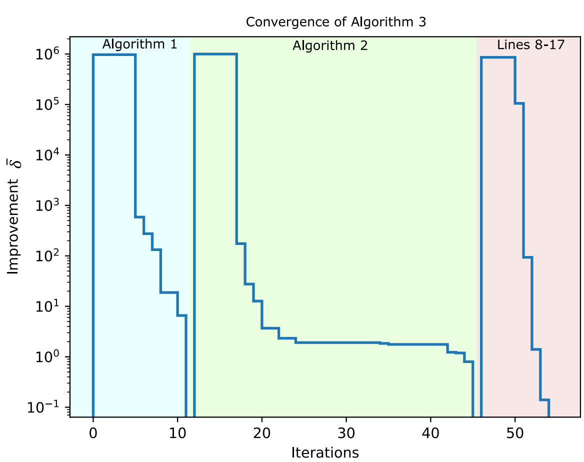


Fig. 7. Convergence process of Case 3 (i.e., Algorithm 3).

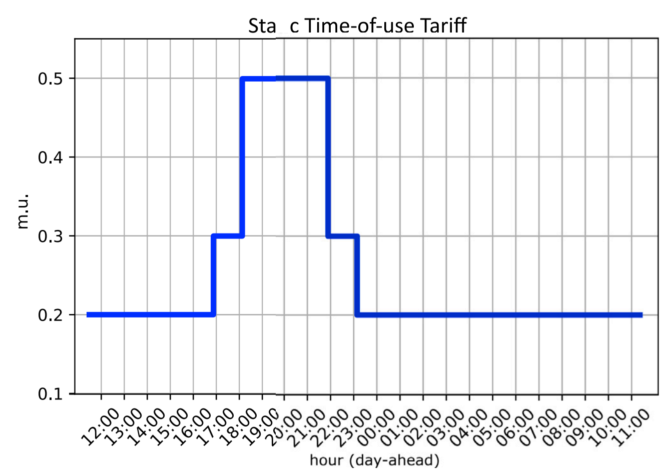


Fig. 8. Time-of-use tariff for the minimal cost-of-energy case.

grid violations by distributing most of the EV charging throughout the night, and maximizes self-sufficiency by "squeezing" the aggregated demand towards zero. Finally, it is important to note that comparing the proposed algorithm with other MAS-based approaches is not justified as others methods either do not account for uncertainty and probabilistic grid limits, or do not involve consensus among prosumers, leading to solutions similar to the un-optimized initial solutions presented in this paper.

Fig. 11 shows the convergence process. As expected, the three iterative processes are performed in sequence. Algorithm 1 (blue zone) for initialization, then Algorithm 2 (green zone) for minimizing grid violations, and then lines 8–17 (red zone) in Algorithm 3 which performs the profile steering with probabilistic grid limits.

4. Conclusions

This paper introduces a new approach for distributed power aggregation within an energy community: stochastic profile steering. Based on a given goal of an aggregator (or the community itself), and by coordinating flexible electricity assets owned by the local prosumers,

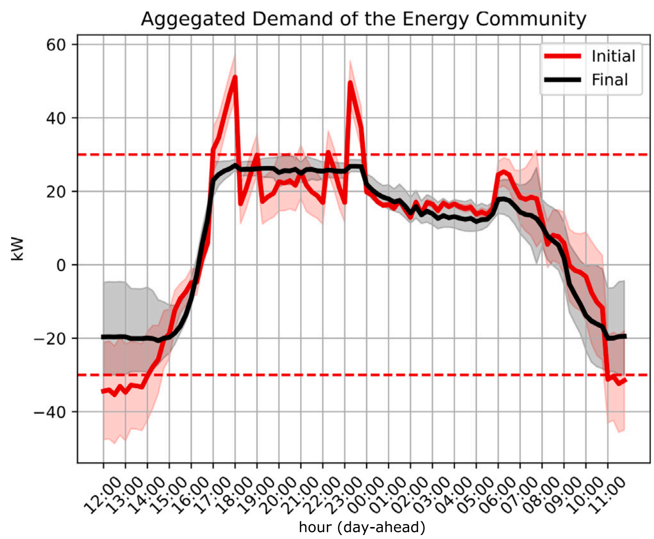


Fig. 9. Initial and optimized aggregated demand of the small energy community for minimal cost-of-energy.

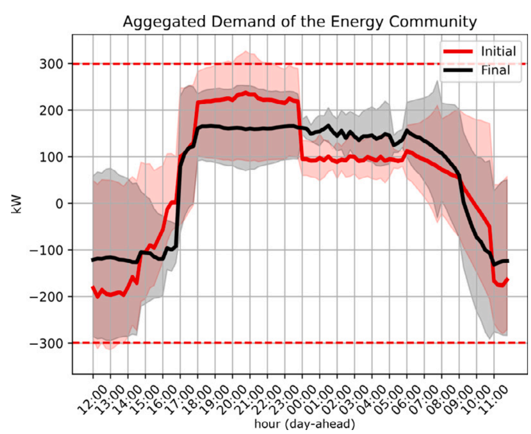


Fig. 10. Initial and optimized aggregated demand of the large energy community for maximal self-sufficiency.

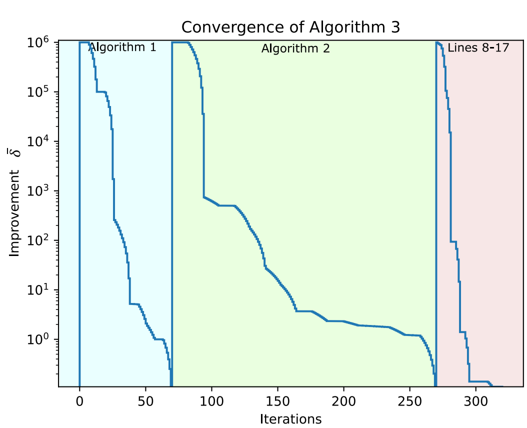


Fig. 11. Convergence process of Algorithm 3 for the large-scale community.

this approach optimizes the average value of the objective function while meeting grid limitations with a given probability. The proposed stochastic version considers local demand, PV production, and EVs as random variables, and its potential is illustrated through simulations of a small (5 households) and a large (100 households) energy community.

Since the proposed method is a greedy heuristic that can optimize the energy community operation even when the local EMS is non-analytical, comparing it with distributed mathematical programming methods, such as ADMM, is unnecessary, as profile steering offers broader applicability. Nevertheless, if the centralized problem formulation is analytical and strictly convex, ADMM should be employed due to its optimality guarantee. However, if this is not the case, the proposed approach is more suitable.

Moreover, the proposed algorithm grows linearly with the number of prosumers and it can be used for different community-level objectives, such as maximum self-sufficiency or minimum aggregated cost-of-energy. Results demonstrate the effectiveness, flexibility, and scalability of the proposed method. Finally, the adaptation of the proposed method for multi-carrier systems, multiple energy communities, and peer-to-peer markets are natural extensions for future research.

CRediT authorship contribution statement

Juan Camilo López: Writing – review & editing, Writing – original draft, Software, Methodology. **Aditya Pappu:** Software, Data curation. **Gerwin Hoogsteen:** Writing – review & editing, Investigation, Conceptualization. **Johann L. Hurink:** Writing – review & editing, Supervision. **Marcos J. Rider:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors of the paper declare no conflicts of interest. No financial, personal, or competing interests exist that could influence the study's outcomes.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the São Paulo Research Funding Agency - FAPESP. Grants 2021/11310-7, 2019/01906-0, and thematic project 2021/11380-5. This project has also received funding from the EU's Horizon 2020 research and innovation program under grant agreement No 101022587, and the Department of Science and Technology (DST), Government of India, under the SUSTENANCE project.

References

[1] Koirala BP, Koliou E, Friege J, Hakvoort RA, Herder PM. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. Renew Sustain Energy Rev 2016;56:722–44. http://dx.doi.org/10.1016/j.rser.2015.11.080.

[2] Mousavi M, Wu M. A DSO framework for market participation of DER aggregators in unbalanced distribution networks. IEEE Trans Power Syst 2022;37(3):2247–58. http://dx.doi.org/10.1109/TPWRS.2021.3117571.

[3] Morstyn T, Teytelboym A, McCulloch MD. Designing decentralized markets for distribution system flexibility. IEEE Trans Power Syst 2019;34(3):2128–39. http://dx.doi.org/10.1109/TPWRS.2018.2886244.

[4] DIRECTIVE (EU) 2018/2001. On the promotion of the use of energy from renewable sources. 2018, URL https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32018L2001&from=EN.

[5] Correa-Florez CA, Michiorri A, Kariniotakis G. Optimal participation of residential aggregators in energy and local flexibility markets. IEEE Trans Smart Grid 2020;11(2):1644–56. http://dx.doi.org/10.1109/TSG.2019.2941687.

[6] Bahloul M, Breathnach L, Cotter J, Daoud M, Saif A, Khadem S. Role of aggregator in coordinating residential virtual power plant in "StoreNet": A pilot project case study. IEEE Trans Sustain Energy 2022;13(4):2148–58. http://dx.doi.org/10.1109/TSTE.2022.3187217.

[7] Utkarsh K, Ding F, Jin X, Blonsky M, Padullaparti H, Balamurugan SP. A network-aware distributed energy resource aggregation framework for flexible, cost-optimal, and resilient operation. IEEE Trans Smart Grid 2022;13(2):1213–24. http://dx.doi.org/10.1109/TSG.2021.3124198.

[8] Olivella-Rosell P, et al. Centralised and distributed optimization for aggregated flexibility services provision. IEEE Trans Smart Grid 2020;11(4):3257–69. http://dx.doi.org/10.1109/TSG.2019.2962269.

[9] Vosoogh M, Rashidinejad M, Abdollahi A, Ghaseminezhad M. An intelligent day ahead energy management framework for networked microgrids considering high penetration of electric vehicles. IEEE Trans Ind Inf 2021;17(1):667–77. http://dx.doi.org/10.1109/TII.2020.2977989.

[10] Favuzza S, Wijethunge AH, Wijayakulasooriya JV, Ekanayake JB, Polpitiya A. Coordinated operation of the constituent components of a community energy system to maximize benefits while considering the network constraints. J Electr Comput Eng 2019. http://dx.doi.org/10.1155/2019/5874962.

[11] Hashemipour N, Granado PCD, Sønju MH. Comparing optimization strategies in local electricity markets. In: 2022 18th international conference on the European energy market. EEM, 2022, p. 1–9. http://dx.doi.org/10.1109/EEM54602.2022.9921146.

[12] Reis IFG, Gonçalves I, Lopes MAR, Henggeler Antunes C. A multi-agent system approach to exploit demand-side flexibility in an energy community. Util Policy 2020;67. http://dx.doi.org/10.1016/j.jup.2020.101114.

[13] Reis IFG, Gonçalves I, Lopes MAR, Henggeler Antunes C. Towards inclusive community-based energy markets: A multiagent framework. Appl Energy 2022;307. http://dx.doi.org/10.1016/j.apenergy.2021.118115.

[14] Simoiu MS, Fagarasan I, Ploix S, Calofir V. Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach. Renew Energy 2022;194:1233–46. http://dx.doi.org/10.1016/j.renene.2022.06.004.

[15] Cai Y, Huang T, Bompard E, Cao Y, Li Y. Self-sustainable community of electricity prosumers in the emerging distribution system. IEEE Trans Smart Grid 2017;8(5):2207–16. http://dx.doi.org/10.1109/TSG.2016.2518241.

[16] Li Y, Ren R, Huang B, Wang R, Sun Q, Gao DW, Zhang H. Distributed hybrid-triggering-based secure dispatch approach for smart grid against DoS attacks. IEEE Trans Syst Man Cybern: Syst 2023;53(6):3574–87. http://dx.doi.org/10.1109/TSMC.2022.3228780.

[17] Liu Y, Gooi HB, Li Y, Xin H, Ye J. A secure distributed transactive energy management scheme for multiple interconnected microgrids considering misbehaviors. IEEE Trans Smart Grid 2019;10(6):5975–86. http://dx.doi.org/10.1109/TSG.2019.2895229.

[18] Li Y, Zhang H, Liang X, Huang B. Event-triggered-based distributed cooperative energy management for multienergy systems. IEEE Trans Ind Inf 2019;15(4):2008–22. http://dx.doi.org/10.1109/TII.2018.2862436.

[19] García-Muñoz F, Dávila S, Quezada F. A benders decomposition approach for solving a two-stage local energy market problem under uncertainty. Appl Energy 2023;329. http://dx.doi.org/10.1016/j.apenergy.2022.1202262.

[20] Xia Y, Xu Q, Tao S, Du P, Ding Y, Fang J. Preserving operation privacy of peer-to-peer energy transaction based on enhanced benders decomposition considering the uncertainty of renewable energy generations. Energy 2022;250. http://dx.doi.org/10.1016/j.energy.2022.123567.

[21] Lilla S, Orozco C, Borghetti A, Napolitano F, Tossani F. Day-ahead scheduling of a local energy community: An alternating direction method of multipliers approach. IEEE Trans Power Syst 2020;35(2):1132–42. http://dx.doi.org/10.1109/TPWRS.2019.2944541.

[22] Crespo-Vazquez JL, AlSkaif T, González-Rueda AM, Gibescu M. A community-based energy market design using decentralized decision-making under uncertainty. IEEE Trans Smart Grid 2021;12(2):1782–93. http://dx.doi.org/10.1109/TSG.2020.3036915.

[23] Alizadeh A, Kamwa I, Moeini A, Mohseni-Bonab SM. An efficient distributed transactive energy control model using adaptive consensus ADMM. In: 2022 10th international conference on systems and control. ICSC, 2022, p. 496–501. http://dx.doi.org/10.1109/ICSC57768.2022.9993910.

[24] Fattaheian-Dehkordi S, Rajaei A, Abbaspour A, Fotuhi-Firuzabad M, Lehtonen M. Distributed transactive framework for congestion management of multiple-microgrid distribution systems. IEEE Trans Smart Grid 2022;13(2):1335–46. http://dx.doi.org/10.1109/TSG.2021.3135139.

[25] Ahmadi SE, Sadeghi D, Marzband M, Abusorrah A, Sedraoui K. Decentralized bi-level stochastic optimization approach for multi-agent multi-energy networked micro-grids with multi-energy storage technologies. Energy 2022;245. http://dx.doi.org/10.1016/j.energy.2022.123223.

[26] Singh A, Sethi BK, Kumar A, Singh D, Misra RK. Three-level hierarchical management of active distribution system with multimicrogrid. Energy 2019;186. http://dx.doi.org/10.1016/j.energy.2019.115873.

[27] Lezama F, Soares J, Hernandez-Leal P, Kaisers M, Pinto T, Vale Z. Local energy markets: Paving the path toward fully transactive energy systems. IEEE Trans Power Syst 2019;34(5):4081–8. http://dx.doi.org/10.1109/TPWRS.2018.2833959.

[28] Alizadeh A, Kamwa I, Moeini A, Mohseni-Bonab SM. Energy management in microgrids using transactive energy control concept under high penetration of renewables; a survey and case study. Renew Sustain Energy Rev 2023;176:113161. http://dx.doi.org/10.1016/j.rser.2023.113161.

[29] Gerards MET, Toersche HA, Hoogsteen G, van der Klauw T, Hurink JL, Smit GJM. Demand side management using profile steering. In: 2015 IEEE Eindhoven powerTech. 2015, p. 1–9. http://dx.doi.org/10.1109/PTC.2015.7232328.

[30] Hoogsteen G, Gerards ME, Hurink JL. On the scalability of decentralized energy management using profile steering. In: 2018 IEEE PES innovative smart grid technologies conference europe. ISGT-europe, 2018, p. 1–9. http://dx.doi.org/10.1109/ISGTEurope.2018.8571823.

[31] Pappu A, Hoogsteen G, Hurink JL. Distributed co-operative demand side management for energy communities. In: 2022 IEEE PES innovative smart grid technologies conference europe. 2022, p. 1–9. http://dx.doi.org/10.1109/ISGT-Europe54678.2022.9960572.

[32] Reis IF, Gonçalves I, Lopes MAR, Henggeler Antunes C. Business models for energy communities: A review of key issues and trends. Renew Sustain Energy Rev 2021;144:111013. http://dx.doi.org/10.1016/j.rser.2021.111013.

[33] Silva JAA, López JC, Arias NB, Rider MJ, da Silva LCP. An optimal stochastic energy management system for resilient microgrids. Appl Energy 2021;300. http://dx.doi.org/10.1016/j.apenergy.2021.117435.

[34] Kaut M. Scenario generation by selection from historical data. Comput Manag Sci 2021;18:411–29. http://dx.doi.org/10.1007/s10287-021-00399-4.

[35] Macedo LH, Franco JF, Rider MJ, Romero R. Optimal operation of distribution networks considering energy storage devices. IEEE Trans Smart Grid 2015;6(6):2825–36. http://dx.doi.org/10.1109/TSG.2015.2419134.

[36] Kim SH, Shin Y-J. Optimize the operating range for improving the cycle life of battery energy storage systems under uncertainty by managing the depth of discharge. J Energy Storage 2023;73:109144. http://dx.doi.org/10.1016/j.est.2023.109144.

[37] Ben-Tal A, Ghaoui LE, Nemirovski A. Robust optimization. Princeton: Princeton University Press; 2009, http://dx.doi.org/10.1515/9781400831050.

[38] Birge J, Louveaux F. Introduction to stochastic programming. Springer series in operations research and financial engineering, Springer New York; 2011.

[39] Wachter A, Biegler LT. On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. Math Program 2005;106:25–57. http://dx.doi.org/10.1007/s10107-004-0559-y.

[40] International Renewable Energy Agency (IRENA). Time-of-use tariffs: innovation landscape brief. 2019, URL https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Feb/IRENA_Innovation_ToU_tariffs_2019.pdf. Accessed: 20.02.2023.